Editorial:

The evolving field of learning analytics research in higher education: From data analysis to theory generation, an agenda for future research

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Over the last decade the deployment and use of learning analytics has become routine in many universities around the world. The ability to analyse the way students interact with technology has demonstrated significant value for providing insights into student learning and there are now a wide range of uses for learning analytics in education. From use as a diagnostic tool, to a method for prediction, learning analytics in higher education has an emphasis on a wide range of outcome measures, including student retention, progression, attainment, performance, mastery, employability and engagement. In exploring how learning analytics can improve learning practice by transforming the ways we support learning processes, this editorial highlights some of the learning analytics research that has been published in AJET to date.

Keywords: Learning Analytics

Introduction

The modern landscape in higher education (HE) is shaped by several critical drivers, including meeting the needs of a diverse group of students, promoting lifelong learning, enhancing student learning experience and widening access (Gašević, Tsai, Dawson, & Pardo, 2019; Siemens, Gašević, & Dawson, 2015). As online learning has succeeded in becoming an integral part this landscape, focus has moved from the use of online technologies to provide *access* to education to the way it can be used to increase education *quality* (Lee, 2017). To this end, Learning Analytics (LA) is increasingly being adopted across the HE sector to better understand and support student learning (Viberg, Hatakka, Bälter, & Mavroudi, 2018).

In the contemporary focus on education quality, the ability to analyse learners' 'digital footprints' (trace data from their interactions with technology) has demonstrated value for providing novel insights into student learning. Access to such data alongside the application of methods drawn from, for example, educational data mining, has shaped the field of LA (Siemens, 2013). Often framed within various learning and cognitive theories associated with educational psychology, cognitive psychology and learning sciences (Gašević et al., 2019), LA is defined by the Society for Learning Analytics Research as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" (Conole, Gašević, Long, & Siemens, 2011).

In the space of a decade, LA in HE has progressed from having a narrow focus on learning and the student experience to one that now includes a greater focus on research, knowledge exchange and praxis (Lang, Siemens, Wise, & Gašević, 2017). While it is still considered to be in its infancy as a research field (Viberg et al., 2018), the topic of LA in HE has already been the focus of a number of literature

reviews (for example see: Avella, Kebritchi, Nunn, & Kanai, 2016; Banihashem, Aliabadi, Ardakani, Delavar, & Ahmadabadi, 2018; El Alfy, Gómez, & Dani, 2019; Ferguson & Clow, 2017; Joksimović, Kovanović, & Dawson, 2019; Leitner, Khalil, & Ebner, 2017; Viberg et al., 2018; Wong, 2017). Such reviews are helpful in defining and positioning this rapidly developing field, however Ferguson and Clow (2017) note that they are largely aimed at researchers and not practitioners. There is also still a sense that while filled with great potential in the HE sector, LA has not yet had widespread or deep impact and many institutions are yet to exploit the full use of learner and organisational data to address institutional and educational challenges (Colvin et al., 2015; Gašević et al., 2019; Higher Education Standards Panel, 2017; Tsai & Gašević, 2017; Tsai et al., 2018).

This editorial highlights some of the LA research that has been published in AJET. While this review is provided in relation to the wider context of research that has explored the evolving field of LA research in HE, it does not claim to be an authoritative, standalone review of the field.

Learning analytics research in higher education contexts

Research into LA in HE has been varied, exploring such issues as: the use of LA as a methodology or tool to address concerns surrounding student retention; predictive analytics (supporting student learning by predicting the future); social learning analytics (understanding student interactions through social network analysis); discourse analytics (understanding student communications); use of LA for supporting student leaning, providing feedback and instructional interventions; and its link with educational theory and learning design (Joksimović et al., 2019). In their review of LA research in HE (2012-2018), Viberg et al., (2018) noted that while the field is still an evolving area of practice and research in which descriptive studies and interpretative data collection methods prevail, there are an increasing number of 'theory use' and 'theory generating' papers indicating that the field is maturing. The authors note that while predictive methods (such as regression and classification, used to predict, for example, performance of students) have been one of the dominating methods in LA research, the proportion of LA studies using predictive statistical methods has decreased. The authors suggest that this, together with an increase in relationship mining methods and a well-established set of methods for the distillation of data for human judgement (statistics and visualisations that help humans make sense of their findings and analyses) indicates that LA research in HE is shifting from prediction of, for example, retention and grades, towards enabling a deeper understanding of students' learning experiences. A search of LA papers in AJET reveals a similar shift.

Learning Analytics research published in AJET

Earlier papers (for example: Kennedy, Ioannou, Zhou, Bailey, & O'Leary, 2013; Oliver & Whelan, 2011; Olmos & Corrin, 2012) published in the journal explored the potential uses of LA to capture learning-related data and convert it into "actionable intelligence" (Olmos & Corrin, 2012, p. 1) for the improvement of teaching and learning. More recently, the emphasis has been on exploring how LA may be integrated with other theories, methods or practices to better understand students' learning experiences and thus better respond to their learning needs. For example, Broadbent (2016) argued that while early analytics research linked students' use of learning management systems (through data as, number of logins, discussion board use, resources used, and time spent on student learning interfaces) with academic performance, psychological factors such as self-efficacy and motivation were much more predictive of student success. She thus suggested that while online behaviour metrics should not be dismissed altogether, a key challenge was to better identify which data could contribute to improving learning models. Recent research has indeed started to explore more deeply how LA may be blended with educational psychology theories to provide researchers and practitioners with various viewpoints on evaluation and thus contribute toward designing effective learning and teaching.

Marzouk et al. (2016) observed that designs for learning often neglect theories in learning science that explain how students learn. The authors therefore argued for the use of learning science in the design of LA. They suggested that research in learning science about goal setting, distributed practice, prior knowledge, feedback and collaborative learning, as well as theories of motivation, self-determination, social cognition and attribution provided strong foundations for designs for LA. This could then guide students towards more effective self-regulated, self-motivated learning. This integration of learning theories into LA research and design has been argued by Wong et al., (2019) and others who emphasise,

for example, the integral role of such theories in providing highly relevant frameworks to guide decisions on the types of data to be collected, the LA approaches to take, and the design and evaluation of tools and interventions. These authors also point out that such theories are important for: informing LA design; contributing to the creation of more meaningful learning experiences, tools, and evidence-based practices; and guiding research into LA that is relevant, operationalizable and credible. Synergies between learning sciences and LA have also been recognised for their potential to advance learning theory and thus are a fruitful area for future research.

In considering how synergies between LA and learning theories may contribute to the educational field, Ifenthaler, Gibson, and Dobozy (2018) observed that the perspectives of learning design and LA had previously operated in a manner that was largely independent of one other, separated by time and space due to the complexity of dealing with interactional data in educational settings. They thus argued for the integration of LA data into the design of learning environments through "learning analytics design" (Ifenthaler, 2017, p. 202) to encourage a future where learning is personalised and adaptive. This convergence and the synergies between the two fields are increasingly recognised as an important area for research. However, while a number of authors have proposed frameworks that connect learning analytics and learning design (for example: Bakharia et al., 2016; Hernández-Leo et al., 2019; Schmitz, Van Limbeek, Greller, Sloep, & Drachsler, 2017), AJET researchers argue that those frameworks are generally at a descriptive levels only, making meaningful operationalisation difficult (Corrin, Law, Ringtved, & Milligna, 2018). Future research thus needs to consider how to better capture and systematise learning analytics data grounded in learning and design theories. This may be achieved through conceptual frameworks that, for example, connect learning design and learning analytics, bridge the gap between theory and practice, and offer guidance in use, interpretation of and reflection on learning analytics for refinement and redesign of learning activities.

AJET authors have also broached the topic of student perspectives in LA. Kitto, Lupton, Davis, and Waters (2017) suggested that despite a narrative that positions LA as a field aiming to enhance student learning, few student-facing solutions have emerged beyond the often-dominant narratives of 'at risk' and 'retention'. West et al. (2020) concurred that much of the literature reflects an academic, teacher-centric or institutional view. In their exploration of the LA literature related to student perceptions on the development and use of LA, the authors found that student perspectives were largely absent from LA development and application. They also found that student-facing dashboards (displays that visualise or present information in a way that allows the end user to quickly make sense of data at a glance) were largely developed from the view of the academic or institution and based on what those academics or institutions thought would be useful for students rather than from a student perspective. While research in the area of student perspectives in LA is growing, West et al. (2020) argue that a lack of input from students raises serious ethical concerns and suggests a need for several actions, including, most prominently, engaging students.

Ethical considerations in the use of LA are of growing concern as the field develops. Commentators have raised concerns about the potential problems associated with the deployment and use of LA (such as privacy, ethics and consent) and the use of big data to "widen the net and thin the mesh to bring greater student regulation and control" (Francis et al., 2019; West et al., 2020). As the ethical considerations behind both the use of student data and the design of analytics systems that use this data are complex, few institutional approaches have, to date, addressed ethical issues in all their complexity (Corrin et al., 2019). As recognised by Downes (2020), the ethics of analytics is particularly complex.With the increased usage of sensitive and personal student data come numerous ethical and privacy issues. Questions continue to arise in relation to whose interests LA operates on and why, how and with what impact; to whom does the data belong; who is allowed to use the data and for what purposes; what happens if a student does not allow his or her data to be used to perform analytics; does the increased access to analytics-based student data and analyses make institutions and educators more accountable; and does the knowledge gained from access to data bring with it a responsibility to act? Further research and practice guidelines need to provide clear answers to these and many similar questions.

Adoption of learning analytics in higher education

Despite the interest that has been shown in LA, many institutions are yet to exploit learner and organisational data fully to address institutional and educational challenges (Gašević et al., 2019; Tsai et

al., 2018). There also remains a lack of institutional examples demonstrating systemic adoption of learning analytics (Gašević et al., 2019) and adoption in everyday classroom practice is still slow (Prieto, Rodríguez-Triana, Martínez-Maldonado, Dimitriadis, & Gašević, 2019). Slow adoption of LA in HE has been a topic that has been explored in three AJET papers. These papers highlight the lack of LA-based solutions to address teaching and learning as well as financial challenges faced by the HE sector.

Problems with teacher participation in LA was identified in a study by West et al. (2016), who found that while teaching staff generally expressed a high level of interest in LA, their participation in LA activities and training was limited. A more recent study by West et al. (2018) also found that using LA is not yet widespread and, as such, it is mostly done in isolation. The authors suggest that while such introspection may be influenced by a lack of LA adoption or the early stage of maturity of LA applications, it means that academics who are interested in LA often pursue their research in isolation and with no clear scope of how LA may be used to drive change. Prieto et al. (2019) observed that adoption of LA in everyday classroom practice remains low. The authors identified the communication difficulties between the stakeholders involved in the process of LA (e.g., teachers, researchers, or technology developers) as the main issue inhibiting LA innovation adoption. In response they proposed the Orchestrating Learning Analytics (OrLA) conceptual framework for use as a tool to support stakeholder communication in any kind of LA adoption process.

While the majority of HE institutions are aware of the benefits provided by the analysis of large-scale data about student learning (Colvin et al., 2016; Gašević et al., 2019; Tsai & Gašević, 2017), the use of LA remains mostly limited to the basic reporting about student engagement (Joksimović et al., 2019). This suggests that most institutions are still in the early stages of adoption and are yet to realise the potential LA can bring. Although a number of frameworks have been developed to address LA adoption in HE (for example: Gašević et al., 2019; Tsai & Gašević, 2017; Tsai et al., 2018), there remains significant opportunity for LA research to facilitate ways for increasing uptake in HE institutions (Colvin et al., 2016; Tsai & Gašević, 2017). Ongoing research into the development and refinement of adoption models and frameworks, such as OrLA by Prieto et al. (2019), is therefore important in aiding the uptake of analytics in HE settings.

Conclusion

Over the last decade, the scope, breadth, depth and complexity of LA in HE has evolved as use and deployment have become more widespread across the sector. There is now more data than ever before, both demographic and behavioural. LA is no longer a side-line activity; there remains concerns about how LA is being adopted throughout the sector. Although this presents huge challenges to individual institutions and the sector more generally, the transformative potential of LA also offers many possibilities for the student learning experiences and outcomes, and for university practices more generally. As HE institutions grapple with questions around how to move the focus of LA towards learning processes rather than learning outcomes, it is essential that researchers continue to explore the nature, deployment and effectiveness of LA in HE.

This editorial reviews some of the LA research published in AJET to date and highlights several research directions for future research. Opportunities lie in strengthening the theoretical lens from which LA should be viewed and the relationships between student data, its analysis for intervention design, and the pedagogy of learning and teaching.

The lack of student voices in LA applications and research, are of concern. While much research has reported LA to be an effective enabler for targeted interventions to students, there is often a lack of evidence for why the intervention worked and how the intervention was perceived from a student's perspective. The concept of student-centred LA is yet to be fully realised by the sector and although some research has been done in this area, too often student-centred LA projects lack student perspective. A lack of student voices also raises ethical concerns about nature and use of LA. The deployment of LA in the HE is a nascent area of research as the ethics of how and why data is collected and used is frequently neglected in the implementation of analytics-based practice.

Finally, because many HE institutions are in the early stages of LA adoption frameworks and initiatives that aid the uptake of analytics in HE settings will continue to be important. To realise its full potential,

LA has to be understood as a continual process of incremental improvement and evolution rather than a one-off effort. In helping to guide the evolution and improvement, ongoing research and development into LA best practices in essential to ensuring the field develops in a manner that is ethical and relevant to educational practice.

AJET seeks contributions addressing any of the LA challenges outlined. Manuscripts with specific focus on the impact of LA on HE are welcome under the current special issue call 'Learning Analytics: Pathways to Impact'. For more information go to https://ajet.org.au/index.php/AJET/SpecialIssueCall.

Acknowledgements

A huge thanks goes to the Associate Editors for their high-quality editorial work that contributes strongly toward our excellent and highly regarded journal. The Associate Editors are highly experienced researchers who expertly shepherd papers through the review process and volunteer their time to the journal.

We thank the AJET copyeditors who work closely with the Lead Editors to ensure a high standard of final proofs is maintained. We also extend heartfelt thanks to our international team of reviewers who perform an invaluable service to the journal.

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Lead Editors Australasian Journal of Education Technology

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Please cite as: Axelsen, M., Redmond, P., Heinrich, E., & Henderson, M. (2020). The evolving field of learning analytics research in higher education: From data analysis to theory generation, an agenda for future research. *Australasian Journal of Educational Technology, 36*(2), 1-7. https://doi.org/10.14742/ajet.5510